



# UNITED STATES PATENT AND TRADEMARK OFFICE

UNITED STATES DEPARTMENT OF COMMERCE  
United States Patent and Trademark Office  
Address: COMMISSIONER OF PATENTS AND TRADEMARKS  
Washington, D.C. 20231  
www.uspto.gov

APPLICATION NO.	FILING DATE	FIRST NAMED INVENTOR	ATTORNEY DOCKET NO.	CONFIRMATION NO.
09/553,956	04/21/2000	Thomas A. Runkler	50277-452	7423

7590 03/25/2003

Stephen C Carlson  
Ditthavong & Carlson P C  
10507 Braddock Road  
Suite A  
Fairfax, VA 22032

EXAMINER	
PHAM, HUNG Q	
ART UNIT	PAPER NUMBER
2172	

DATE MAILED: 03/25/2003

Please find below and/or attached an Office communication concerning this application or proceeding.

# Office Action Summary

Application No.

09/553,956

Applicant(s)

RUNKLER ET AL.

Examiner

HUNG Q PHAM

Art Unit

2172

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

## Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If the period for reply specified above is less than thirty (30) days, a reply within the statutory minimum of thirty (30) days will be considered timely.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133).
- Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

## Status

- 1) ☒ Responsive to communication(s) filed on 03 February 2003.
- 2a) ☒ This action is **FINAL**.                      2b) ☐ This action is non-final.
- 3) ☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

## Disposition of Claims

- 4) ☒ Claim(s) 1-34 is/are pending in the application.
- 4a) Of the above claim(s) \_\_\_\_\_ is/are withdrawn from consideration.
- 5) ☐ Claim(s) \_\_\_\_\_ is/are allowed.
- 6) ☒ Claim(s) 1-34 is/are rejected.
- 7) ☐ Claim(s) \_\_\_\_\_ is/are objected to.
- 8) ☐ Claim(s) \_\_\_\_\_ are subject to restriction and/or election requirement.

## Application Papers

- 9) ☐ The specification is objected to by the Examiner.
- 10) ☐ The drawing(s) filed on \_\_\_\_\_ is/are: a) ☐ accepted or b) ☐ objected to by the Examiner.
- Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).
- 11) ☐ The proposed drawing correction filed on \_\_\_\_\_ is: a) ☐ approved b) ☐ disapproved by the Examiner.
- If approved, corrected drawings are required in reply to this Office action.
- 12) ☐ The oath or declaration is objected to by the Examiner.

## Priority under 35 U.S.C. §§ 119 and 120

- 13) ☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).
- a) ☐ All   b) ☐ Some \* c) ☐ None of:
1. ☐ Certified copies of the priority documents have been received.
2. ☐ Certified copies of the priority documents have been received in Application No. \_\_\_\_\_.
3. ☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).
- \* See the attached detailed Office action for a list of the certified copies not received.
- 14) ☐ Acknowledgment is made of a claim for domestic priority under 35 U.S.C. § 119(e) (to a provisional application).
- a) ☐ The translation of the foreign language provisional application has been received.
- 15) ☐ Acknowledgment is made of a claim for domestic priority under 35 U.S.C. §§ 120 and/or 121.

## Attachment(s)

- 1) ☐ Notice of References Cited (PTO-892)
- 2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
- 3) ☐ Information Disclosure Statement(s) (PTO-1449) Paper No(s) \_\_\_\_\_.
- 4) ☐ Interview Summary (PTO-413) Paper No(s). \_\_\_\_\_.
- 5) ☐ Notice of Informal Patent Application (PTO-152)
- 6) ☐ Other: \_\_\_\_\_.

## DETAILED ACTION

### *Response to Arguments*

1. Applicants amended claims 1, 9, 18, and 28 in the amendment received on 02/03/2003. The pending claims are 1-34. Applicants' arguments have been fully considered but they are not persuasive.

As argued by applicants in page 12 of the amendment:

Claims 1 and 18 recites a way of refining a node in a decision tree by selecting a feature of those that characterize the data associated with the node, then performing a cluster analysis along the selected feature, and then constructing arcs of the decision tree for each of the clusters. Thus, a cluster analysis is performed in refining a node in a decision tree, enabling the decision to be built "on the fly" (see Spec., p. 6).

By contrast, Hall et al. does not show this way of building a decision tree, by performing a cluster analysis in refining a node of a decision tree. Rather, Hall et al. is directed to a method of developing of fuzzy rules from continuous valued data by building a decision tree in accordance with the C4.5 algorithm (Abstract, p. 1757, col. 1).

However, Hall et al. recognize that the "C4.5 algorithm tree **algorithm requires crisp** class assignments for all objects. It is **necessary** to partition the continuous output values into a effect set of **discrete output** classes." (Section 2.1, p. 1758, col. 1, emphasis added). Accordingly, Hall et al. propose to preprocess the data first by applying a fuzzy c-means clustering to determine the discrete classes, and then feeding the discrete classes into the C4.5 algorithm: "After a discrete class has been created for each example, as discussed in Section 2.1, C4.5 may be used to create a decision tree." (Section 3, p. 1759, col. 1).

Accordingly, Hall et al. fails to teach or suggest "performing a cluster analysis along the selected feature to group the data into one or more clusters" since whatever cluster analysis that is performed in Hall et al. is performed before building the decision tree, that is, without selecting a feature when refining a node of a decision tree. The remaining references, Shafer et al. and Choe et al., also fail to teach this aspect of claims 1-9 and 18-26.

Examiner respectfully traverses because of these reasons:

As shown in table 1 of page 1757, a training set from the domain of tennis to determine whether to play tennis based on the Weather: (Sunny, Cloudy), Wind (Windy, Quiet), Temperature (0, 100° F) and there are two outcomes (Play, Don't Play). Given the training example to C4.5, the simple decision tree in page 1758, FIG. 1 would be

produced. The decision tree allows the classification of examples into  $n$  classes ( $n = 2$  here) by choosing an attribute whose values may split the examples up into more homogeneous groups, and in this example, the attribute Temperature is chosen to associate with the root node (Decision trees from C4.5, page 1757) indicates the step of *selecting a feature from among the features characterizing the data associated with the node*. Hall further discloses that the attribute values of a continuous valued attribute are each examined as a possible attribute to split the example set of a node in a decision tree and a value in the data set is chosen as the "split point" (Decision trees from C4.5, pages 1757-1758). In here, the continuous valued attribute is *temperature*, and its values are examined in order to cluster the data into two groups, one with temperature  $\leq 80$  and one with temperature  $> 80$ . This technique indicates the step of *performing a cluster analysis along the selected feature to group the data into one or more clusters*.

Examiner agrees with the applicants' argument that Hall et al. is directed to a method of developing of fuzzy rules from continuous valued data by building a decision tree in accordance with the C4.5 algorithm (Abstract, p. 1757, col. 1). However, the technique of creating a decision tree as disclosed by Hall as discussed above is implemented by the C4.5 learning system before the fuzzy rules could be extracted from the decision tree (page 1757, Introduction).

As argued by applicants in page 13 of the amendment:

*Hall et al.*, alone or in combination with *Shafer et al.* and *Choe et al.*, fail to teach or suggest the limitations of claims 2-3, 10-17, 19-20, and 27-34. For example, independent claims 10 and 27 recite: performing a plurality of cluster analyses along each of the features to calculate a **maximal cluster validity measure**, said maximal cluster validity measure corresponding to one of the features; selecting the one of the features corresponding to the maximal cluster validity measure;

Dependent claims 2 and 19 also affirmatively recite these limitations. None of the references show the recited "maximal cluster validity measure" calculated by performed a plurality of cluster analyses and selecting one of the features that corresponds to the maximal cluster validity measure. Moreover, claims 3, 11, 17, 20, 27, and 34 specify a specific kind of maximal cluster validity measure that based on the "partition coefficient."

As explained above, *Hall et al.* discloses a method of generating fuzzy rules from data by first performing a fuzzy cluster analysis to determine crisp, discrete classes for the data and then applying the *C4.5* decision tree algorithm to the discrete classes. Since the *C4.5* decision tree algorithm requires discrete classes, the *C4.5* algorithms selects its features to build the decision tree based on the "highest information gain associated with it" (Section 2, p. 1758, col. 1)-but not on a "maximal cluster validity measure" or a "partition coefficient" based on performing cluster analyses as recited in the claims.

Examiner respectfully traverses because of these reasons:

As disclosed by Hall, the training set is given to *C4.5* as the decision tree learning system. The attribute values of a continuous valued attribute are each examined as a possible attribute to split the example set of a node in a decision tree. The selection of a specific value is based upon the information gain ratio associated with choosing that attribute. The attribute, which has the highest information gain, is chosen as the attributes for splitting the examples at a node (Decision trees from *C4.5*, pages 1757-1758). As claimed by the applicants, the maximal cluster validity measure as defined in claims 10 and 27 is just a variable that *correspond to one of the features*, and *one of the features corresponding to the maximal cluster validity measure is selected for subdividing the data into one or more groups based on the selected feature*. Thus, the maximum information gain still satisfies the condition of the claimed maximal cluster validity measure. In addition, the maximum information gain is chosen among the calculated information gain ratios as *the partition coefficients*.

As argued by applicants in page 14 of the amendment with regards to claims 7-8, 15, 24-25, and 32. Examiner respectfully traverses because Choe teaches a clustering

Art Unit: 2172

criterion based on an error tolerance  $\epsilon$  as *a predetermined threshold* by calculating a cluster center to update a fuzzy c-partition U, if the different between two consecutive U is less than or equal the error tolerance as *a predetermined relationship*, the data is grouped into the cluster (Choe, Fuzzy C-Means Algorithm, ALGORITHM 1, Step 6). Thus, instead of the different between two consecutive U, a domain ratio could be used and still give the same result.

### ***Claim Rejections - 35 USC § 103***

2. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

(a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negated by the manner in which the invention was made.

This application currently names joint inventors. In considering patentability of the claims under 35 U.S.C. 103(a), the examiner presumes that the subject matter of the various claims was commonly owned at the time any inventions covered therein were made absent any evidence to the contrary. Applicant is advised of the obligation under 37 CFR 1.56 to point out the inventor and invention dates of each claim that was not commonly owned at the time a later invention was made in order for the examiner to consider the applicability of 35 U.S.C. 103(c) and potential 35 U.S.C. 102(e), (f) or (g) prior art under 35 U.S.C. 103(a).

**3. Claims 1-5, 9-13, 16-22, 26-30 and 33-34 are rejected under 35 U.S.C. 103(a) as being unpatentable over Hall et al. [Generating Fuzzy Rules from Data].**

Regarding to claims 1 and 18, Hall teaches a method of developing fuzzy rules from continuous valued data by exploiting the properties of decision trees, a crisp decision tree is created by creating a discrete set of fuzzy output classes and providing a set of training example to the decision tree learning system (abstract). Hall does not explicitly teach the steps of *selecting a feature from among the features characterizing the data associated with the node; performing a cluster analysis along the selected feature to group the data into one or more clusters; and constructing one or more arcs of the decision tree at the node respectively for each of the one or more clusters*. However, as shown in table 1, a training set from the domain of tennis to determine whether to play tennis based on the Weather: (Sunny, Cloudy), Wind (Windy, Quiet), Temperature (0, 100° F) and there are two outcomes (Play, Don't Play). The training set is given to C4.5 as the decision tree learning system. The decision tree allows the classification of examples into two classes and each class is associated with a node of the tree by choosing an attribute whose values may split the examples up into more homogeneous groups and as shown in FIG. 1, the attribute Temperature is chosen (Decision trees from C4.5, page 1757) as the step of *selecting a feature from among the features characterizing the data associated with the node*. Hall further discloses that the attribute values of a continuous valued attribute are each examined as a possible attribute to split the example set of a node in a decision tree and a value in the data set is chosen as the

“split point” (Decision trees from C4.5, pages 1757-1758) as the step of *performing a cluster analysis along the selected feature to group the data into one or more clusters*. As shown in FIG. 1, the root node of the tree is labeled *Temperature* and indicates that the temperature of the weather is tested. The right arc that connects the *Temperature* node to leaf node *No Play* is labeled  $> 80$  indicating that leaf node *No Play* is to be reached if the temperature is greater than 80. On the other hand, the left arc connects *Temperature* node to another branch node is labeled  $\leq 80$  indicating the branch node is to be reached if the temperature is  $\leq 80$ . The branch node is labeled *Wind*. Thus, the technique as shown in FIG. 1 indicates the step of *constructing one or more arcs of the decision tree at the node respectively for each of the one or more clusters*. Therefore, it would have been obvious for one of ordinary skill in the art at the time the invention was made to modify the Hall method of generating a decision tree by including the steps of selecting a feature, performing cluster analysis, constructing one or more arcs of the decision tree in order to classify records of unknown class.

Regarding to claims 2 and 19, Hall teaches all the claimed subject matters as discussed in claims 1 and 18, Hall further discloses the steps of *performing a plurality of cluster analyses along each of the features to calculate a maximal cluster validity measure, said maximal cluster validity measure corresponding to one of the features; and selecting the one of the features that corresponds to the maximal cluster validity measure* (Decision trees from C4.5, pages 1757-1758).



Regarding to claims 3 and 20, Hall teaches all the claimed subject matters as discussed in claims 2 and 19, Hall further discloses the step: *for each of the features, performing a plurality of cluster analyses along said each of the features for a plurality of cluster numbers to calculate respective partition coefficients; and determining the maximal cluster validity measure from among the partition coefficients* (Decision trees from C4.5, pages 1757-1758).

Regarding to claims 4 and 21, Hall teaches all the claimed subject matters as discussed in claims 1 and 18, Hall further discloses the step of *performing the cluster analysis includes the step of performing a fuzzy cluster analysis* (Decision trees from C4.5, pages 1757-1758).

Regarding to claims 5 and 22, Hall teaches all the claimed subject matters as discussed in claims 4 and 21, Hall further discloses the step of *performing the fuzzy cluster analysis includes the step of performing a fuzzy c-means analysis* (Creating class labels and FCG, pages 1758-1760).

Regarding to claims 9 and 26, Hall teaches all the claimed subject matters as discussed in claims 1 and 18, Hall further discloses the steps of *projecting the data in each of the clusters, wherein the projected data are characterized by the plurality of the features but for the selected feature; and recursively performing the steps of selecting a*

*feature and performing the cluster analysis on the projected data in each of the clusters* (FIG. 1, Decision trees from C4.5, pages 1757-1758).

Regarding to claims 10 and 27, Hall teaches a method of developing fuzzy rules from continuous valued data by exploiting the properties of decision trees; a crisp decision tree is created by creating a discrete set of fuzzy output classes and providing a set of training example to the decision tree learning system (abstract). Hall does not explicitly teach the steps of *performing a plurality of cluster analysis along the selected feature to calculate a maximal cluster validity measure, said maximal cluster validity measure corresponding to one of the features; selecting the one of the features corresponding to the maximal cluster validity measure; subdividing the data into one or more groups based on the selected feature; and building the decision tree based on the one or more groups*. However, as shown in table 1, a training set from the domain of tennis to determine whether to play tennis based on the Weather: (Sunny, Cloudy), Wind (Windy, Quiet), Temperature (0, 100° F) and there are two outcomes (Play, Don't Play). The training set is given to C4.5 as the decision tree learning system. The decision tree allows the classification of examples into two classes by choosing an attribute whose values may split the examples up into more homogeneous groups. The attribute values of a continuous valued attribute are each examined as a possible attribute to split the example set of a node in a decision tree. The selection of a specific value is based upon the maximum information gain ratio associated with choosing that attribute. The attribute, which has the highest information gain associated with it is chosen as the attribute for splitting the

Art Unit: 2172

examples at a node (Decision trees from C4.5, pages 1757-1758 and FIG. 1). This technique indicates the step of *performing a plurality of cluster analysis along the selected feature to calculate a maximal cluster validity measure, said maximal cluster validity measure corresponding to one of the features; selecting the one of the features corresponding to the maximal cluster validity measure*. As shown in FIG. 1, based on the maximum information gain of 0.459 using 80 as the split point, the decision tree is produced as the step of *subdividing the data into one or more groups based on the selected feature; and building the decision tree based on the one or more groups*. Therefore, it would have been obvious for one of ordinary skill in the art at the time the invention was made to modify the Hall method of generating a decision tree by performing a cluster analysis, selecting the feature based on maximal cluster validity measure and subdividing the data in order to classify records of unknown class.

Regarding to claims 11 and 28, Hall teaches all the claimed subject matters as discussed in claims 10 and 27, Hall further discloses the step: *for each of the features, performing a plurality of cluster analyses along said each of the features for a plurality of cluster numbers to calculate respective partition coefficients; and determining the maximal cluster validity measure from among the partition coefficients* (Decision trees from C4.5, pages 1757-1758).

Regarding to claims 12 and 29, Hall teaches all the claimed subject matters as discussed in claims 10 and 27, Hall further discloses the step of *performing the cluster*

*analysis includes the step of performing a fuzzy cluster analysis* (Decision trees from C4.5, pages 1757-1758).

Regarding to claims 13 and 30, Hall teaches all the claimed subject matters as discussed in claims 10 and 27, Hall further discloses the step of *performing the fuzzy cluster analysis includes the step of performing a fuzzy c-means analysis* (Creating class labels and FCG, pages 1758-1760).

Regarding to claims 16 and 33, Hall teaches all the claimed subject matters as discussed in claims 10 and 27, Hall further discloses the steps of *projecting the data in each of the group, wherein the projected data are characterized by the plurality of the features but for the selected feature; and recursively performing the steps of selecting a feature, comprising selecting a new one of the features corresponding to a new maximal partition coefficient and subdividing the data into one or more new groups based on the selected new feature* (FIG. 1, Decision trees from C4.5, pages 1757-1758).

Regarding to claims 17 and 34, Hall teaches a method of developing fuzzy rules from continuous valued data by exploiting the properties of decision trees; a crisp decision tree is created by creating a discrete set of fuzzy output classes and providing a set of training example to the decision tree learning system (abstract). As shown in table 1, a training set from the domain of tennis to determine whether to play tennis based on the Weather: (Sunny, Cloudy), Wind (Windy, Quiet), Temperature (0°, 100°F)

Art Unit: 2172

and there are two outcomes (Play, Don't Play). The training set is given to C4.5 as the decision tree learning system. The decision tree allows the classification of examples into two classes by choosing an attribute whose values may split the examples up into more homogeneous groups. The attribute values of a continuous valued attribute are each examined as a possible attribute to split the example set of a node in a decision tree. The selection of a specific value is based upon the maximum information gain or *maximal partition coefficient* (Decision trees from C4.5, pages 1757-1758) as the step of *performing a plurality of fuzzy cluster analysis along each of the features to calculate a maximal partition coefficient and a corresponding set of one or more fuzzy clusters, said maximal partition coefficient corresponding to one of the features*. As illustrated in FIG. 1, the attribute Temperature is chosen with the maximum information gain of 0.459 as the step of *selecting the one of the features corresponding to the maximal partition coefficient*. As shown in FIG. 1, based on the maximum information gain of 0.459 using 80 as the split point, the decision tree is produced as the step of *building the decision tree based on the corresponding set of one or more fuzzy clusters*. Therefore, it would have been obvious for one of ordinary skill in the art at the time the invention was made to modify the Hall method of generating a decision tree by performing a fuzzy cluster analysis and selecting the feature based on maximal partition coefficient and in order to classify records of unknown class.

**4. Claims 6, 14, 23 and 31 are rejected under 35 U.S.C. 103(a) as being unpatentable over Hall et al. [Generating Fuzzy Rules from Data] in view of Shafer et al. [SPRINT: A Scalable Parallel Classifier for Data Mining].**

Regarding to claims 6, 14, 23 and 31, Hall teaches all the claimed subject matters as discussed in claims 1, 10, 18 and 27, but fails to disclose the step of *performing the cluster analysis includes the step of performing a hard cluster analysis*. Shafer teaches a method of forming a decision tree by performing a hard cluster analysis (Shafer, SPRINT: A scalable Parallel Classifier for Data Mining, pages 544-550, especially Abstract and Introduction pages 544-545). Therefore, it would have been obvious for one of ordinary skill in the art at the time the invention was made to modify the Hall method by including the technique of hard cluster analysis in order to optimize the system by using a regular cluster for classifying records of unknown class.

**5. Claims 7-8, 15, 24-25 and 32 are rejected under 35 U.S.C. 103(a) as being unpatentable over Hall et al. [Generating Fuzzy Rules from Data] in view of Choe et al. [On the Optimal Choice of Parameters in a Fuzzy C-Means Algorithm].**

Regarding to claims 7, 15, 24 and 32, Hall teaches all the claimed subject matters as discussed in claims 1, 10, 18 and 27, but fails to disclose the steps of *calculating a domain ratio of a difference in domains limits of the data over a difference in domain limits of a superset of the data; determining whether the domain ratio has a*

*predetermined relationship with a predetermined threshold; and if the domain ratio has the predetermined relationship with the predetermined threshold, then grouping the data into a single cluster.* Choe teaches a clustering criterion based on an error tolerance  $\epsilon$  as a *predetermined threshold* by calculating a cluster center to update a fuzzy c-partition U, if the different between two consecutive U is less than or equal the error tolerance as a *predetermined relationship*, the data is grouped into the cluster (Choe, Fuzzy C-Means Algorithm, ALGORITHM 1, Step 6). Thus, instead of the different between two consecutive U, a domain ratio could be used and still give the same result. Therefore, it would have been obvious for one of ordinary skill in the art at the time the invention was made to modify the Hall method by using a domain ration in order to cluster data in a finite set.

Regarding to claims 8 and 25, Hall and Choe teaches all the claimed subject matters as discussed in claims 7 and 24, Choe further discloses the step of *determining whether the domain ratio is less than the predetermined threshold* (Choe, Fuzzy C-Means Algorithm, ALGORITHM 1, Step 6).

### **Conclusion**

**6. THIS ACTION IS MADE FINAL.** Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).


A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within

TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the mailing date of this final action.

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Hung Pham whose telephone number is 703-605 4242. The examiner can normally be reached on Monday-Friday, 7:00 Am - 3:30 Pm.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, VU, KIM YEN can be reached on 703-305 4393. The fax phone numbers for the organization where this application or proceeding is assigned are 703-746 7239 for regular communications and 703-746 7238 for After Final communications. Any inquiry of a general nature or relating to the status of this application or proceeding should be directed to the receptionist whose telephone number is 703-305 3900.

Examiner: Hung Pham  
March 19, 2003

  
KIM VU  
SUPERVISORY PATENT EXAMINER  
TECHNOLOGY CENTER 2100